Shell Companies: Using a hybrid technique to detect illicit activities

Tiwari, Milind; Gepp, Adrian; Kumar, Kuldeep

Recommended citation(APA):
Tiwari, M., Gepp, A., & Kumar, K. (2021). *Shell Companies: Using a hybrid technique to detect illicit activities*. Poster session presented at 2021 Accounting and Finance Association of Australia and New Zealand (AFAANZ) Virtual Conference.

2021 AFAANZ Virtual Conference

Shell Companies: Using a hybrid technique to detect illicit activities

Milind Tiwari, Adrian Gepp, Kuldeep Kumar

Bond University

ABSTRACT

Shell companies can be used to launder dirty money to make it appear legitimate and hide information about the actual beneficial owners. Illegal arms dealers, drug cartels, corrupt politicians, terrorists and cyber-criminals have become some of the frequent users of shell companies. This study aims to develop a model for detecting shell companies being used to launder illicit proceeds of crime using a new hybrid statistical approach. Using a combination of graph algorithms and supervised learning, detection models with classification accuracy ranging between 88.17% and 97.85%, were developed to detect illicit entities. To the best of our knowledge, no prior study exists on developing quantitative models to detect illicit shell companies using publicly available information. The key stakeholders to benefit from such models would be legal and compliant professionals and government officials, especially accountants, tax officials and anti-corruption NGOs.

AIM AND MOTIVATION

- The study aims to facilitate the detection of money laundering activities by using graph analysis with publicly available data on entities identified in several corruption cases to develop a detection model. The opportunity rests in using the networks prevalent among entities in a corrupt network and analysing the links and similarities. The analysis would facilitate scores which could be useful in distinguishing corrupt entities from the non-fraudulent ones.
- Shell Companies have legitimate uses such as facilitating reverse mergers, being used as a holding company or for protecting small entrepreneurs from bankruptcy risks. However, these entities have become instruments to launder money and hide information about beneficial owners. Illegal arms dealers, drug cartels, corrupt politicians, terrorists and cyber-criminals have become some of the frequent users of these shell companies.
- The use of shell companies to evade taxes has been examined in the literature (Compin 2008; Sikka and Willmott 2010). In 2002, an anonymous shell corporation called Anglo-Leasing was used to launder €24 million as part of the contract awarded to firm to update the passport system in Kenya. The information about the beneficial owners could not be identified because of the anonymity provided to this form of entity (Findley, Nielson, and Sharman 2015; Allred et al. 2017). The International Consortium of Investigative Journalists (ICIJ) in its report highlighted the intensive usage of shell companies by politically exposed persons (PEPs), to hold wealth in offshore centres (Harding 2016).

GRAPHS AND NEO4J

- Graph analysis may enable investigators effortlessly to infer ownership and relationships, for example, common or joint ownership of businesses, and hence detect these illicit shells. Graph networks have been used by investigative journalists to examine hidden links between illicit companies (Battaglia et al. 2018; Liu et al. 2016).
- Graph analysis techniques help to handle a large volume of data efficiently (Liu et al. 2016). Besides, the visualization of dynamic and complex data in the form of graphs lead users to have a detailed overview of the data, filter, select and investigate networks details. It is in line with the observations of Singh and Best (2016) who state that approaches reducing the burden of excessive information may help identify suspicious activities and may contribute to the effectiveness of anti-money laundering effort.
- Neo4J, a graph database platform, was chosen to develop graphs from the collected data. It involves the use of a query language called 'Cypher' and lends flexibility in setting up the data model. The flexibility in setting up the data structure exposes hidden relationships in the data and allows conclusions to be drawn accordingly (Van Bruggen 2014). Moreover, graph query languages such as 'Cypher', with different levels of expressivity, serves as a function for querying graphs for data. It facilitates the application of single-relational network algorithms to complex network data.

DATA AND METHODOLOGY

- For this study, 208 limited companies were considered (initially there were 210, but two were duplicates). The names were provided by Transparency International, UK (TIUK), an anti-corruption non-governmental organization (NGO), (Cowdock 2017). To determine the usefulness of the detection mechanism, a matching sample of 205 (initially 207 companies, but again, two were found to be duplicates) limited companies were considered.
- The entities in the matching sample may be involved in illicit activities. However, in line with the assumptions of Ravenda et al. (2015), it is assumed that a low probability exists for an entity chosen from the large population of companies registered with the corporate registry (in this case the UK Companies House) to be involved in illicit activity.
- The data on these entities were obtained from OpenCorporates through a data cleansing and wrangling tool called OpenRefine. Information about the appointment of directors was obtained from the UK Companies House. Finally, other information sources considered for this study were EveryPolitician (to reconcile if director was a politician), OpenSanctions (to check for sanctioned individuals), UK Companies House Disqualified Directors Dataset (see if any disqualified directors) and the Financial Secrecy Index (to see ranking of jurisdictions of executive's citizenship).
- Once collected and imported, the data were analyzed using several graph algorithms, mainly related to determining similarities, communities, and node importance. One of the underlying rationales was to establish a base for the interaction between network structure and node attributes rather than just considering the importance of nodes in a network for analysis (Backstrom and Leskovec 2010). The scores were the results of these graph analytics and were further exported to decision-tree software called CART (Classification and Regression Trees) provided exclusively by Salford Systems. The methodology and network topology adopted has been depicted in the figure below.

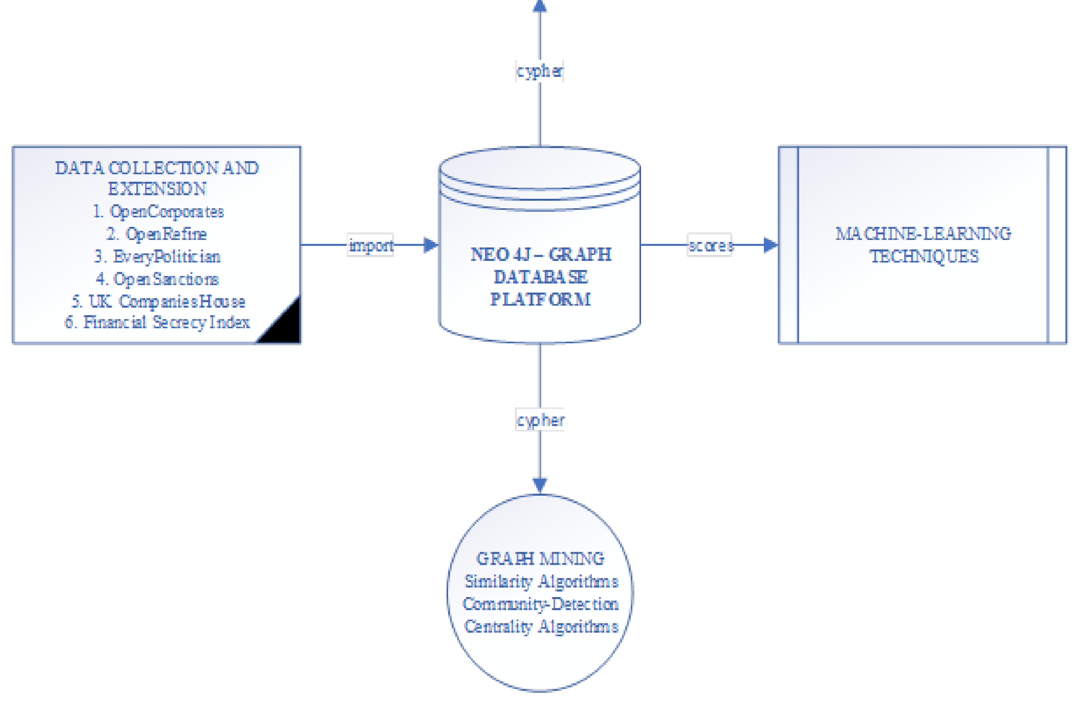

Fig.1: Methodology

FINDINGS AND IMPLICATIONS

- The paper uses various combinations of similarity, community-detection and centrality algorithms (namely, Jaccard Index, Overlap Index, Triangles and Triangle Counting Algorithm, Betweenness Centrality, Approximate Betweenness-Centrality and Harmonic Centrality algorithm).
- The results showed that on using three classification algorithms, namely Decision Trees, TreeNet, and Random Forests, for the combination of various graph algorithms, the classification accuracy achieved was within the range of 88.17 % and 97.85 %, respectively.
- The performance of these algorithms was regarded using different performance metrics like Area under ROC (AUC), precision, recall and F-value. The scores obtained using various combinations of graph algorithms were used for the classification models to compare the performance and determine whether the classification accuracy is consistent across them. The literature is consistent with use of these measures to evaluate performance (Kute et al. 2021). The lack of any work in the academic literature on detection of shell companies using publicly available information prohibits comparison to evaluate the performance of the present methodology. However, the present work lays down a benchmark for comparison for future studies.
- This study has implications for anti-corruption NGOs, corporate registries, financial institutions, government officials, legal and compliance professionals, especially tax-officials and accountants. For anti-corruption NGOs, corporate registries and government officials, such a model would suggest a move towards the incorporation of graph database platform aimed at identifying hidden relationships between entities. For financial institutions with access to transaction information, use of such detection models would aid in filing Suspicious Activity Reports (SARs). The role of accountants is vital in reporting money laundering activities (Mitchell, Sikka, and Willmott 1998b) and use of such models would help them continue to do so.

NOVELTY AND CONTRIBUTION

- Attempts towards identifying shell companies being used for illicit activities such as bribery, corruption, and money laundering are in the nascent stage.
- A study identified to have taken a step in this direction was Luna et al. (2018). The lack of accessible real banking transaction data prompted the authors to develop a banking transaction simulator for shell and regular companies. Anomaly detection techniques were used to detect variations between expected and observed business transaction profiles of legitimate and shell companies. The rationale was to identify shell companies that could be investigated further for any illicit activity. However, the model focused only on banking transactions and therefore did not use publicly available information such as the number of directors and their backgrounds and whether transactions were made to tax havens or countries with a weak banking regime.
- The present study makes use of such information. The opportunity rests in using the networks prevalent among entities in a corrupt network and analysing the links and similarities. In Australia, the amount of money being laundered annually was estimated between AUD 10-15 billion per annum. Therefore, the present work contributes to address such a problem by presenting a measure for detection of entities used to launder funds.

- Allred, B. B., Findley, M. G., Nielson, D., & Sharman, J. C. (2017). Anonymous Shell Companies: A Global Audit Study and Field Experiment in 176 Countries. *Journal of International Business Studies, 48*(5), 596-619.
- Battaglia, P. W., Hamrick, J. B., Bapst, V., Sanchez-Gonzalez, A., Zambaldi, V., Malinowski, M., . . . Pascanu, R. (2018). Relational inductive biases, deep learning, and graph networks. *arXiv e-prints*. Retrieved from https://ui.adsabs.harvard.edu/abs/2018arXiv180601261B
- Compin, F. (2008). The role of accounting in money laundering and money dirtying. *Critical Perspectives on Accounting, 19*(5), 591-602. doi:10.1016/j.cpa.2007.01.001
- Cowdock, B. (2017). *Hiding in Plain Sight: How UK Companies are used to launder corrupt wealth*. Retrieved from United Kingdom: http://www.transparency.org.uk/publications/hiding-in-plain-sight/#.WwInj3eFO70
- Findley, M. G., Nielson, D. L., & Sharman, J. C. (2015). Causes of noncompliance with international law: A field experiment on anonymous incorporation. *American Journal of Political Science, 59*(1), 146-161. doi:10.1111/ajps.12141
- Harding, L. (2016). What are the Panama Papers? A guide to history's biggest data leak. *The Guardian*. Retrieved from http://www.theguardian.com/news/2016/apr/03/what-you-need-to-know-about-the-panama-papers
- Kute, D. V., Pradhan, B., Shukla, N., & Alamri, A. (2021). Deep learning and explainable artificial intelligence techniques applied for detecting money laundering – a critical review. *Ieee Access*, 1-1. doi:10.1109/ACCESS.2021.3086230
- Liu, J., Bier, E., Wilson, A., Guerra-Gomez, J. A., Honda, T., Sricharan, K., . . . Davies, D. (2016). Graph analysis for detecting fraud, waste, and abuse in healthcare data. *AI Magazine, 37*(2), 33-46.
- Luna, D. K., Palshikar, G. K., Apte, M., & Bhattacharya, A. (2018). *Finding shell company accounts using anomaly detection*. Paper presented at the Proceedings of the ACM India Joint International Conference on Data Science and Management of Data, Goa, India.
- Mitchell, A., Sikka, P., & Willmott, H. (1998). Sweeping it under the carpet: The role of accountancy firms in moneylaundering. *Accounting, Organizations and Society, 23*(5), 589-607. doi:10.1016/S0361-3682(98)00010-5
- Singh, K., & Best, P. (2016). Interactive visual analysis of anomalous accounts payable transactions in SAP enterprise systems. *Managerial Auditing Journal, 31*(1), 35-63. doi:10.1108/MAJ-10-2014-1117
- Sikka, P., & Willmott, H. (2010). The dark side of transfer pricing: Its role in tax avoidance and wealth retentiveness. *Critical Perspectives on Accounting, 21*(4), 342-356. doi://doi.org/10.1016/j.cpa.2010.02.004